1. What is the optimal value of alpha for ridge and lasso regression? What will be the changes in the model if you choose double the value of alpha for both ridge and lasso? What will be the most important predictor variables after the change is implemented?

Ans. Optimal value of alpha for Ridge and Lasso is .0001 and 2.0 respectively. Below table shows predictor variable

Changes in model if alpha value is doubles
When alpha increases regularization becomes stricter, resulting in reduction in variance, increase in bias, and model becomes simpler. In lasso in significant beta coefficients will be marked as zeros while in Ridge beta coefficients will be push almost near to zero for less significant features.

Lasso: if alpha is doubled from .0001 then below are the changes in the model

1. Top five predictor variable changes and beta coefficient values also changes
2. Beta βo value increases when alpha is doubled. At alpha .0001 βo 0.08221185291665678
   At alpha .0002 βo 0.12212948359222042
3. In the Lasso regression model, the beta coefficients of less significant features are identified as zero. Notably, when the alpha parameter is doubled, there is a corresponding increase in the number of zero beta coefficients.
   at an alpha value of 0.0001, zero beta coefficient count is 77
   at an alpha value of 0.0002, zero beta coefficient count is 108
4. R2 score of training and test has decreased slightly, while RSS, MSE and RMSE values has increased slightly
5. At alpha .01 model becomes too simple to capture relevance. This can be observed in scatter plot

Most Important predictor after change implemented

Alpha: 0.0001

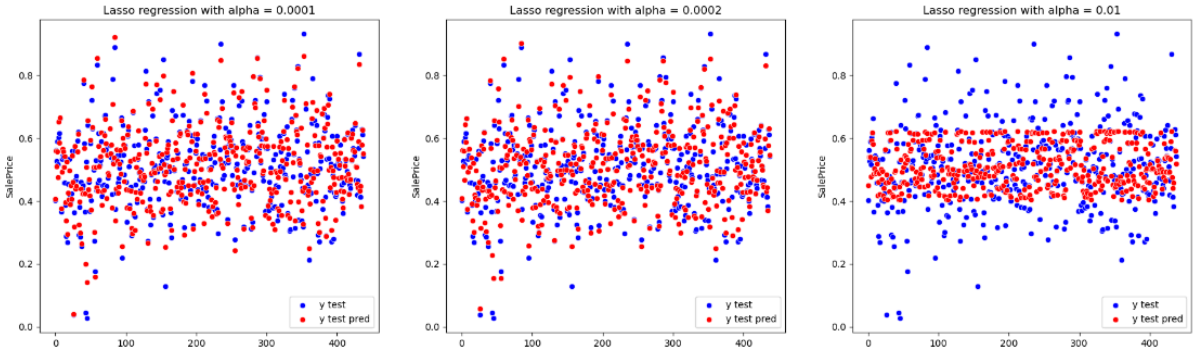
beta	features
0.308287	GrLivArea
0.162438	OverallQual
0.094896	OverallCond
0.078638	GarageCars
0.056504	MSZoning_RL

Alpha: 0.0002

beta	features
0.302146	GrLivArea
0.180248	OverallQual
0.091497	OverallCond
0.078666	GarageCars
0.052211	BsmtFullBath

Alpha:	0.0001 Lasso	0.0002 Lasso
MSE Test	0.001999	0.002030
MSE Train	0.001383	0.001549
R2_score Test	0.885180	0.883405
R2_score Train	0.916848	0.906895
RMSE Test	0.044710	0.045055
RMSE Train	0.037189	0.039352
RSS Test	0.875573	0.889112
RSS Train	1.412076	1.581093

Alpha .0001 (best) Alpha= .0002 Alpha= .01



Ridge: if alpha is doubled from the 2 to 4 the below are the changes in model.

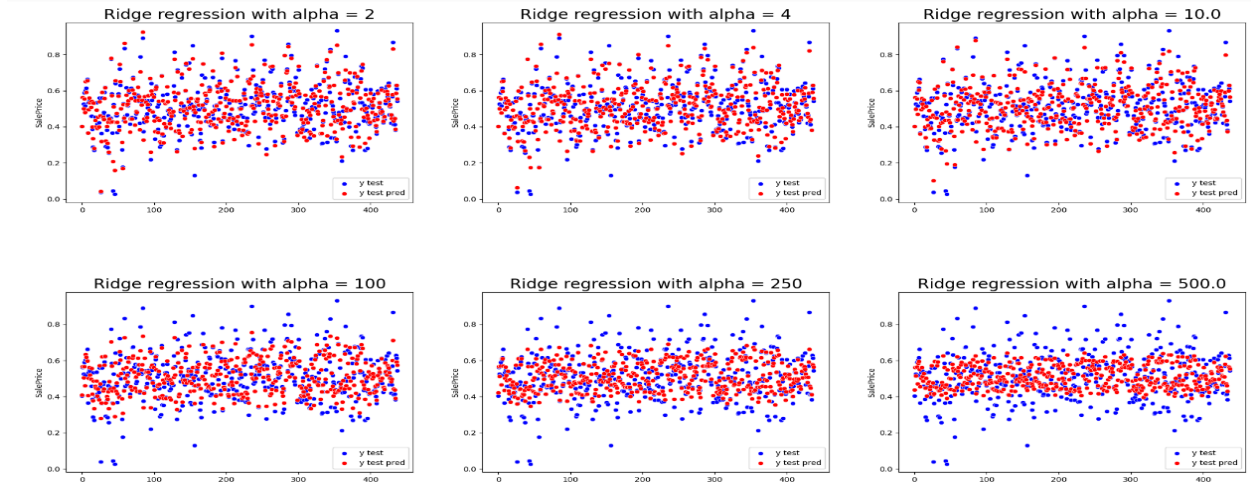
1. Complexity of model gets reduced, variance gets decreased
2. Beta coefficient of predictor variable changes
3. Beta coefficient βo 0.17220026207707828 at alpha = 4
   Beta coefficient βo 0.12498451745924394 at alpha =2

4. R2 score of training and test has decreased slightly, while RSS, MSE and RMSE values has increased slightly

Most Important predictor after change implemented

alpha=2		alpha=4	
features	**beta**	**features**	**beta**
OverallQual	0.128202	OverallQual	0.113936
GrLivArea	0.095476	GrLivArea	0.079324
1stFlrSF	0.083750	OverallCond	0.070593
OverallCond	0.079901	1stFlrSF	0.067578
2ndFlrSF	0.063707	2ndFlrSF	0.057371

	alpha=2 Ridge	alpha=4 Ridge
MSE Test	0.002110	0.002128
MSE Train	0.001325	0.001402
R2_score Test	0.878812	0.877759
R2_score Train	0.920344	0.915709
RMSE Test	0.045934	0.046133
RMSE Train	0.036399	0.037443
RSS Test	0.924136	0.932163
RSS Train	1.352706	1.431412



The reason of not having significant observable variation in model performance with increase in alpha from 2 to 100, while there is a sfinificant difference in model performance from alpha 100 onwards, could be due to the dataset containing large number of features, some of which may not be highly relevant.

By increasing alpha, Ridge regression reduces (approx near to zero) the magnitude of coefficients associated with less important features, which can help in reducing model variance without substantially increasing bias. However, it's important to note that while the coefficients for less relevant features are reduced, they are not set to zero.

with increase of alpha r2 score and other parameter also changes, out of these parameters alpha 2 is the best

Question 2
You have determined the optimal value of lambda for ridge and lasso regression during the assignment. Now, which one will you choose to apply and why?

Answer
Below is the table based on which model is selected
Best alpha value for Lasso is .0001 and Ridge is 2

	Linear Regression	Lasso	Ridge
MSE Test	3.324731e+20	0.001999	0.002110
MSE Train	1.451160e-03	0.001383	0.001325
R2_score Test	-1.909659e+22	0.885180	0.878812
R2_score Train	9.127515e-01	0.916848	0.920344
RMSE Test	1.823385e+10	0.044710	0.045934
RMSE Train	3.809409e-02	0.037189	0.036399
RSS Test	1.456232e+23	0.875573	0.924136
RSS Train	1.481634e+00	1.412076	1.352706

Based on the provided table, the Lasso regression model appears to be the most suitable choice for several reasons:

1. **MSE (Mean Squared Error)**: Lasso has the lowest MSE on the test set, indicating it performs better on unseen(test) data than Ridge and significantly better than Linear Regression.Ridge has the lowest MSE on the training set, but the differences between Lasso and Ridge are minimal.
Lower MSE indicates better model performance with fewer errors.

2. **R2 Score**: The R2 score reflects the proportion of the variance in the dependent variable that is predictable from the independent variable(s). Max R2 score can be 1.
Lasso has the highest R2 score on the test set, suggesting it explains the variation in the target variable better than Ridge and far better than Linear Regression.

3. **RMSE (Root Mean Squared Error)**: Lower is better. Lasso has the lowest RMSE on the test set, further confirming its better performance in generalizing to unseen data. Ridge has the lowest RMSE on the training set, suggesting a slightly better fit to the training data compared to Lasso.

4. **RSS (Residual Sum of Squares)**: Lower is better. Lasso has a lower RSS on the test set compared to Ridge, indicating it has less residual variance. Ridge has the lowest RSS on the training set, suggesting it fits the training data slightly better.

Lasso's and Ridge's performance is relatively close across all metrics. The **Lasso model is the best choice** due to its lowest MSE and RMSE, highest R2 scores, and reduced RSS, indicating better accuracy, fit, and predictive efficiency on unseen (**test**) data. It effectively reduces overfitting by nullifying less relevant features.

Question 3
After building the model, you realised that the five most important predictor variables in the lasso model are not available in the incoming data. You will now have to create another model excluding the five most important predictor variables. Which are the five most important predictor variables now?

Answer
Based on the Lasso regression as it was the best model, the five most important predictor variables are determined by their coefficient values (which represent the strength and nature of the relationship with the dependent variable), are:

Below are the top five predictor with their beta coefficients
At best alpha .0001

	beta	independentVariable
14	0.308287	GrLivArea
3	0.162438	OverallQual
4	0.094896	OverallCond
22	0.078638	GarageCars
31	0.056504	MSZoning_RL

After removing above top five predictor *below are new top five predictors according to Lasso at alpha .0002. Although removing top parameters did reduce the R2 Score*

1. **1stFlrSF (0.248370):** First-floor square footage, indicating that larger first floors are associated with an increase in the (SalesPrice) dependent variable.
2. **2ndFlrSF (0.131027):** Second-floor square footage, suggesting that larger second floors also contribute significantly to the (SalesPrice) dependent variable.
3. **GarageArea (0.079007):** The area of the garage in square feet, which shows a substantial positive impact on the (SalesPrice) dependent variable.
4. **TotRmsAbvGrd (0.060334596):** Total rooms above grade (excluding bathrooms), indicating that a higher number of rooms is positively associated with the (SalesPrice) dependent variable.
5. **Neighbourhood_crawfor(0.050909):** A dummy variable indicating whether the property is in the Crawford neighborhood, suggesting a positive effect on the (SalesPrice) dependent variable when the property is located in this area.

These variables represent the most significant predictors in the model, highlighting the importance total room above grade , of property size (as measured by square footage and the number of rooms) and Full Bathoom condition in influencing the dependent variable.

At best alpha .0002

	beta	independentVariable
10	0.248370	1stFlrSF
11	0.131027	2ndFlrSF
19	0.079007	GarageArea
16	0.060334	TotRmsAbvGrd
40	0.050909	Neighborhood_Crawfor

Question 4
How can you make sure that a model is robust and generalisable? What are the implications of the same for the accuracy of the model and why?

Answer
To guarantee a model is robust and generalisable, several approaches and factors must be considered. These are intended to boost the model's performance on unseen data, rather than just on the specific dataset on which it was trained.

1. **Data Quantity, Quality and Diversity:** The model ought to be developed using ample, diverse, high-quality data that accurately reflects the problem domain. Such variety aids in creating a model capable of better generalization across various scenarios, thereby enhancing model's prediction.

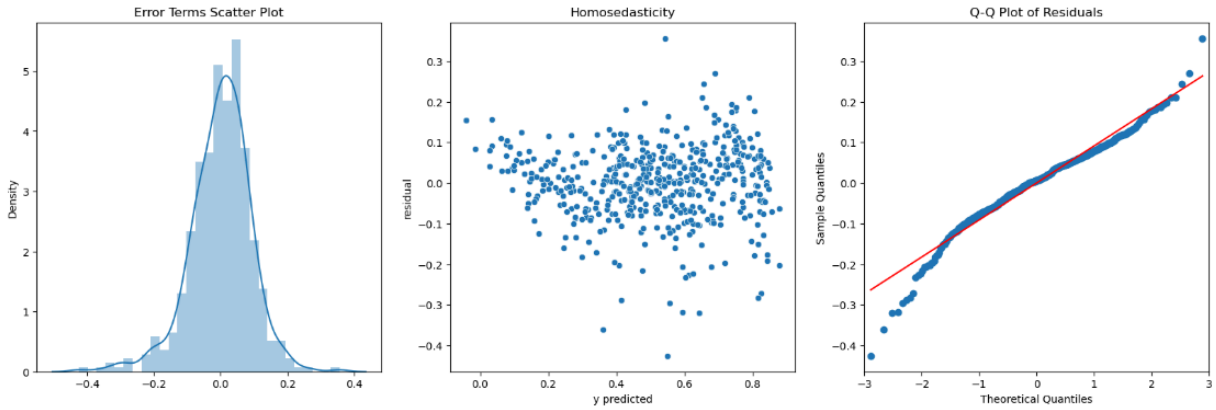
2. **Cross-validation:** Employ cross-validation methods in the training phase, like k-fold cross-validation. This method splits the data into k segments and conducts k rounds of training. In each round, a distinct segment is used for validation, while the rest serve as the training dataset. This approach aids in evaluating the model's efficacy over various data subsets, improving its ability to generalize and offering a better prediction of its performance on new, unobserved data.

3. **Regularization**: Regularization employs methods like Lasso and Ridge. Lasso drives the beta coefficients of less important features to zero, thus simplifying the model and lowering its variance. On the other hand, Ridge regularization nudges the beta coefficients of lesser significant features towards zero as much as possible. These strategies help avoid the model become overfitted, which could degrade its ability to perform well on novel, unseen data..

4. **Model Complexity**: (**Larger the lambda simpler the model)-** Choose the hyper parameter to appropriately. We can use metric such as MSE,RMSE,RSS and R2_Score to identify which lambda results in better metric values. For overfittrf models there is a huge reduction in R2_Score from training to test.

5. **Feature Selection and EDA**: Thoughtfully choose and derive features that will contribute to predictive power of model. This process may include eliminating unnecessary features, developing new ones that highlight crucial trends, and applying normalization or standardization to the data. Skillful feature engineering can enhance the model's precision and its capacity to generalize effectively.

6. **Linear Regression assumption verification**: Once a model is build, we can plot error terms (residuals) to identify is there is homocedasticty (constance variance and no pattern in error terms). Error terms should follow normal curve and centered around zero.



7. **Monitoring and Updating**: Continuously monitor the model's performance in real-world applications and update it with new data. This ensures the model remains relevant and accurate over time as the underlying data distributions change.

The effects of these approaches on model accuracy are subtle. Techniques such as regularization and choosing a model of suitable complexity may marginally lower the model's accuracy on the training dataset by averting overfitting. However, these methods are vital for making sure that the model excels with new, unseen data, providing a more accurate measure of its real-world accuracy and usefulness. Striking a balance between closely fitting the training data and preserving the model's generalization capability is crucial for creating models that are both robust and precise.